A COMPREHENSIVE STOCHASTIC MODEL OF BLIND USAGE: THEORY AND VALIDATION

Frédéric Haldi[1] and Darren Robinson[1]

[1] Solar Energy and Building Physics Laboratory,
Ecole Polytechnique Fédérale de Lausanne,
Station 18, CH-1015 Lausanne, Switzerland.

ABSTRACT

Based on six years of continuous measurements, we have analysed in detail the occupancy, thermal and visual parameters influencing blind usage behaviour. This paper begins by presenting some of the key findings from these analyses. Informed by other developments in the literature, we go on to propose an approach for a comprehensive stochastic model for simulating blind usage.

INTRODUCTION

Past research in the domain of occupants' actions on blinds was based on two motivations: first, the development of control algorithms to allow automated systems to adjust shading in order to optimise solar heat gains and visual comfort; second, the prediction of actions performed by occupants in order to integrate them into building simulation tools. We are interested here in the latter approach. To this end we briefly review here previously published findings.

Based on analysis of variance of two months measurements in a building, Rea (1984) observed that blind occlusion varied significantly between different sky conditions (cloudy or clear), the building orientation (east, south and west) and the interactions between the levels of these latter variables. He noticed that occupants made apparently little attempt to change blinds positions during the day.

From measurements on four buildings, Inoue et al. (1988) noticed that the frequency of blind usage varied with orientation and weather conditions and that it was very particular to the building surveyed. They concluded that if the direct solar radiation on a façade exceeded some value between 12 and 58 W/m^2, blind occlusion is then proportional to sunlight penetration depth.

Reinhart et al. (2002) developed the Lightswitch-2002 algorithm, which dynamically models manual and automatic control of blinds and lights on a 5 minutes time step, and was integrated into ESP-r. This model distinguishes two types of behaviour towards blinds use: dynamic (adjusted on a daily basis) and static (permanently lowered). For this blinds are lowered if the irradiance on the workplace reaches the threshold of 50 W/m^2; they are otherwise kept open. Lightswitch-2002 appears to be the first attempt to develop a formal algorithm for the prediction of actions on blinds. It does nevertheless have some limitations: it predicts that blinds are opened only once a day and it uses a rigid threshold for visual comfort.

Nicol and Humphreys (2004) mentioned an increase in the proportion of blinds lowered as indoor (and outdoor) temperature rises. However, they go on to suggest that the effect seems marginal and that it may simply reformulate the effect of a primary variable linked to visual stimuli. Instead, they recommend the use of outdoor illuminance as the explanatory variable.

In their pilot study Sutter et al. (2006) observed that occupants mostly set their blinds fully raised or lowered. They also reported an "hysteresis phenomenon" in the use of blinds; that is the illuminance level at which occupants lower their blinds is higher than that at which they raise them. It was noticed that most occupants keep their blinds down until the illuminance is very low, before raising them. They observed that a logit distribution – with the logarithm of external vertical global illuminance as driving variable – fits well the percentage of blinds raised. The possibility of an independent effect of temperature was also suggested.

Using Bayesian analysis, Lindelöf (2008) analysed actions on blinds performed in the LESO building (see next section) to infer a probability distribution of visual discomfort that reaches a minimum for horizontal workplane illuminance of 800 to 1200 lux.

Mahdavi (2008) observed from a field survey in three buildings, that actions on shading devices occurred on average once every week, with significant differences between occupants.

Finally, based on measurements in two air-conditioned buildings, Inkarojrit (2008) tested a model formulated as logit probability distributions, with a range of different parameters; finally retaining four predictors: average luminance of the window, maximum luminance of the window, vertical solar radiation and self-reported sensitivity to brightness. The experimental design did not however support the development of a comprehensive model, as only the behaviour on arrival is studied.

This short review underlines the need for further research in order to correctly integrate occupants' behaviour with respect to blinds, as the majority of published studies have not been supported by the data required to infer comprehensive models (or the opportunity for doing so has not been taken). The only complete approach (Reinhart, 2002) is dampened by the somewhat restrictive assumptions mentioned earlier. In order to fill this gap, we propose to develop a comprehensive model including interaction probabilities based on suitably chosen driving variables – an approach providing suitable integration into dynamic building simulation programs.

THE FIELD SURVEY

We present here the experimental design that provided the basis for the development of our models, together with a description of the building in which data were collected.

Figure 1 General view of the LESO building

Data used here were collected from the Solar Energy and Building Physics Laboratory (LESO-PB) experimental building, located in the suburb of Lausanne, Switzerland (46°31'17"N, 6°34'02"E, alt. 396 m). In every office, occupants have the possibility to control two external blinds: a lower blind potentially covering the totality of the vision window and an upper blind covering an anidolic system. These blinds are controlled by switches allowing occupants to shade any desired fraction. Six offices are occupied by two persons, where one of them can directly control the blinds, while eight offices accommodate single occupants. Figure 1 shows a general view of the building.

All 14 south-facing cellular offices of this building have been equipped with sensors whose real-time measurements are archived by a centralised EIB data acquisition system. For a period covering 1 January 2004 to 1 April 2009 (with the exception of a few short interruptions caused by maintenance and technical reasons), local indoor temperature, occupancy, indoor horizontal illuminance on the workplane, outdoor global horizontal illuminance, outdoor global and diffuse horizontal irradiance were continuously measured. Two offices have a very particular configuration of blinds and so were removed from the database.

Outdoor temperature was measured by a sensor located on the roof from 17 March 2005. In parallel, a weather station located 7.7km away records, every 10 minutes, measurements of temperature and global irrandiance.

As noted above, local outdoor climate data are missing for the first year of measurements. To rectify this, linear regression between local and meteorological data for the period with data was used to extrapolate from meteorological measurements for the period without local data.

PRELIMINARY OBSERVATIONS

We present here a few preliminary observations of interest for the development of a model. The statistical software R was used for all data analyses and for the programming of models.

Occupancy-related effects

We observe that 24.1% of actions on blinds take place on arrival, while 10.6% occur at departure, if we define these transitions by 5 minutes thresholds (Figure 2). This shows that actions occur more often than average on arrival. Furthermore, it has to be checked whether this is an intrinsic effect of occupancy transition (eg. the occupant feels a sudden difference in the visual environment, motivating action), or whether it is more likely that the blind position is inadequate after an unoccupied period du to climatic changes.

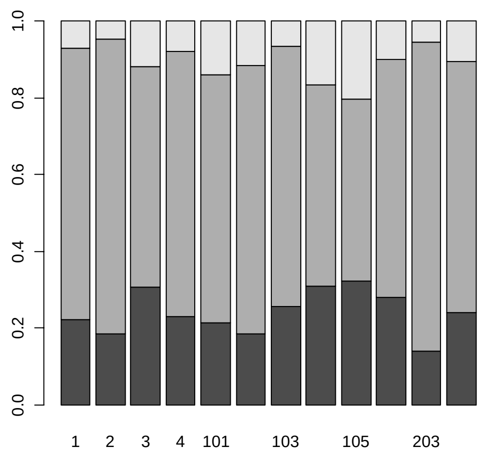

Figure 2 Proportion of actions on blinds performed on arrival (dark gray), during presence (gray) and at departure (light gray) for different offices

On the contrary, there is no significant increase in action rate when occupants leave their offices. Occupants thus do not seem therefore to adjust their blinds for predictive purposes, for instance to prevent excess solar gains during their absence. This fact may advocate for the use of an automatic controller to optimise heat gains during occupants' absence.

This data also suggests that actions on blinds are less occupancy-dependent than actions on windows (see Haldi and Robinson 2009). Finally, we do not observe significant differences in behaviour between offices and between floors (Figure 2).

Average shaded fraction

We observed that occupants set their blinds most of the time to be fully lowered or fully raised. The blinds covering the lower part of the window were fully raised 67.1% of occupied time and fully lowered 5.2%. We show in Figure 4 the observed frequencies of shaded fractions for these lower blinds.

However, this pattern may be due to the fact that blinds are set in movement by pressing a command, while another press is needed for stopping it. We may expect a different behaviour for other types of command, such as crank-operated shading devices.

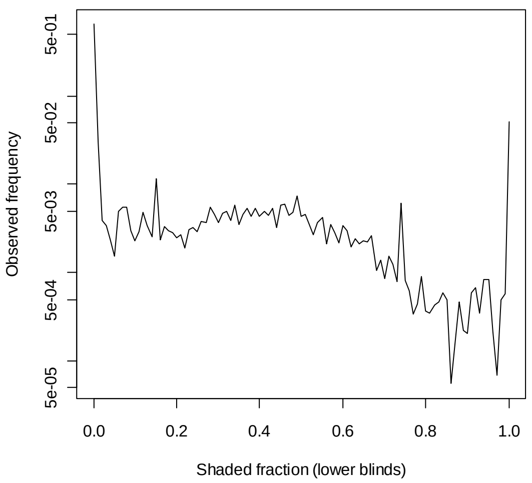

Figure 4 Observed frequencies of shaded fractions by lower blinds (logarithmic scale)

Dominant parameters for actions

Before formally inferring a model for the probability of raising and lowering blinds, we studied the contributions of several variables of interest, when actions occur. We show in Figure 5 the distribution of indoor illuminance, indoor temperature, sun elevation and azimuth at the moment of lowering (left) and raising (right).

From this we observe a clear differentiation with respect to indoor horizontal illuminance. For lowering actions a local maximum is reached near 1200 lux. Coherently, raising actions are more typical of low illuminance values, so that the maximum occurs at 200 lux. The position of the sun also seems to influence actions. For lowering we attain maxima near ϕ = 20° and α = 150° and 200°, which may correspond to typical angles of sun visibility from the south façade. Raising actions reach peaks around ϕ = 15° and α = 240°, which typically corresponds to the end of afternoon. No clear differentiation is evident from the distribution of θ_{in}; in both cases we have maxima near 24°C.

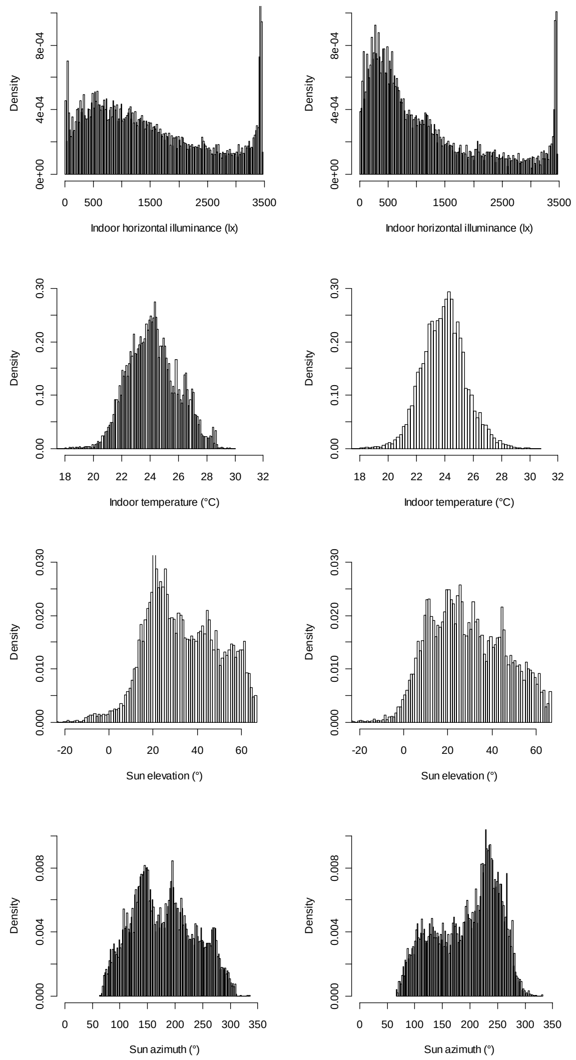

Figure 5 Distribution of several variables when lowering (left) and raising (right) blinds

This shows that E_{in}, ϕ and α are correlated with actions on blinds. However, they are inter-correlated and a careful variable selection procedure must confirm the existence of their independent contributions.

ORDINAL LOGISTIC REGRESSION

An interesting approach to infer a distribution predicting the state of blinds with respect to their shaded fraction is to perform ordinal logistic regression. The classical logit distribution, linking a binary outcome with a set of predictors, was previously used to provide a probability distribution for a window to be open or a blind to be lowered. However, the outcome is here not formally binary, as a shaded fraction can take any value between 0 and 1.

For this the proportional odds model gives a probability for the shaded fraction S to be at least a fraction j as the function:

$$P(S \geq j \mid X) = \frac{1}{1+\exp(-(\alpha_j + X\beta))}, \quad (1)$$

where j = 0, 0.01, …, 1. With this convention, we have a regression parameter β_i per predictor and an intercept α_j per threshold shaded fraction. We performed this procedure with several variables of interest, see Figure 6 for graphical results with indoor temperature and outdoor global irradiance.

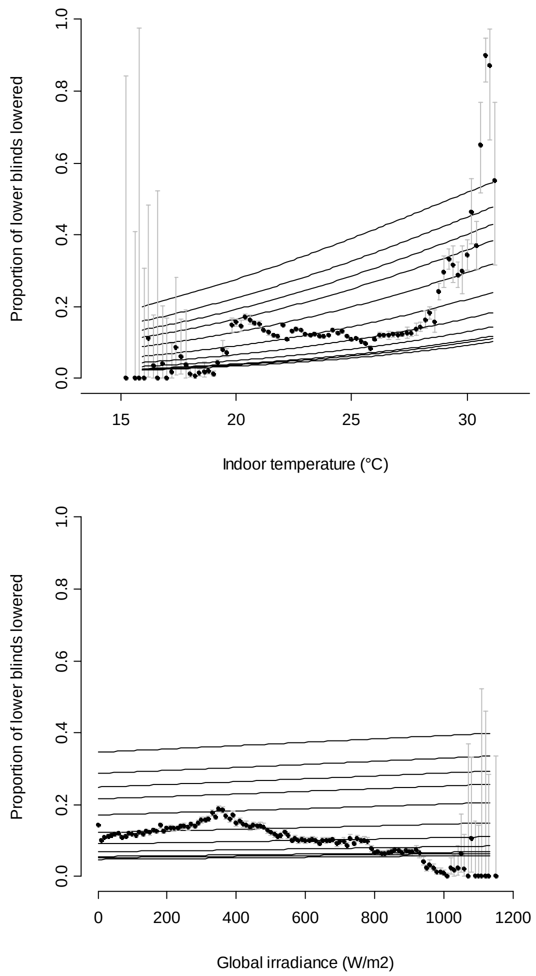

Figure 6 Observed proportion of blinds shading at least half of the window, with binomial confidence interval and ordinal logistic regression curves for each 10% shaded fractions

The obtained distributions efficiently summarise the typical shaded fractions with respect to a chosen predictor. However, they do not describe the dynamics of actions and their application with Monte-Carlo simulation is not straightforward.

DISCRETE-TIME MARKOV PROCESS

In order to account for the real dynamic processes leading occupants to perform actions on blinds, we try to infer actual probabilities of lowering or raising blinds, provided relevant physical parameters, determined through statistical analysis of observations.

Our approach is first to determine the driving variables influencing actions and then to formulate lowering and raising probabilities. Based on the observed over-representation of actions on arrival, we will distinguish occupancy situations (arrived, intermediate, departing) and check for the significance of their differences.

From now on, we use the following notation for all the models based on logit distributions:

$$\text{logit}(p) = \log(p/(1-p)) = a + b_{\text{in}}\,\theta_{\text{in}} + b_{\text{out}}\,\theta_{\text{out}} + b_{\text{E}}\,E_{\text{in}} + b_{\text{Eout}}\,E_{\text{out}} + b_{\text{Igh}}\,I_{\text{gl,hor}} + b_{\text{Idh}}\,I_{\text{diff,hor}} + b_{\text{Ib}}\,I_{\text{beam}} + b_{\text{SL}}\,S_{\text{low}} + b_{\text{SU}}\,S_{\text{up}} + b_{\text{L}}\,f_{\text{L}}, \quad (1)$$

where a and b_i are the regression parameters (see the nomenclature for other definitions). Further details regarding the principles of logistic regression may be found in Hosmer and Lemeshow (2000).

Following from univariate models we proceeded to consider models with several variables and assess the increased predictive value of more complex models. We then determined the best model containing two variables and identified the significance of the added variable as well as the stability of the primary variable; continuing this procedure to other predictors until no further addition may provide extra significance. This procedure is known as forward selection.

Actions on arrival on the lower blinds

Occupants lowered their blinds upon 2.3% of their arrivals and raised them for 1.4% of them. The best model for lowering actions on arrival with a single predictor uses indoor horizontal illuminance as the driving variable. We obtain thus logit(p) = $a + b_E E_{in}$, with a = -3.379±0.027 and b_E = (-3.13±0.2481)·10^{-4}. We see in Figure 2 that observed proportions of lowering actions are well fitted by this curve.

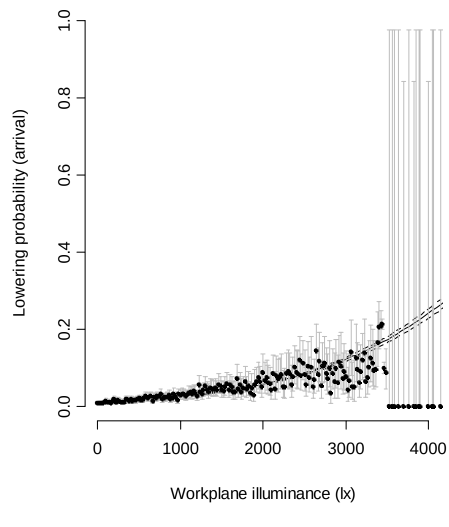

Figure 2 Observed proportion of lowering actions on arrival as a function of indoor illuminance, with 95% level confidence intervals and logistic regression curves

Proceeding to consider a second variable we observe that the shaded fraction before action S_{low} induces the greatest increase in predictive accuracy (Table 1). Other variables do not bring any significant contribution if used as a third predictor.

Table 1
Goodness-of-fit estimators (area under ROC curve, Nagelkerke's R^2, Brier score and Somers' D_{xy}) for lower blinds logistic models

VARIABLES	AUC	R^2	B	D_{XY}
$P_{lower,arr}$				
E_{in}	0.763	0.128	0.034	0.526
E_{in}, S_{low}	0.781	0.147	0.033	0.561
$P_{raise,arr}$				
E_{in}	0.570	0.009	0.025	0.140
S_{low}	0.921	0.303	0.022	0.842
S_{low}, E_{in}	0.921	0.309	0.022	0.841
$P_{lower,int}$				
E_{in}	0.748	0.061	0.004	0.495
E_{in}, S_{low}	0.748	0.066	0.004	0.495
$P_{raise,int}$				
S_{low}	0.855	0.079	0.004	0.709
S_{low}, E_{in}	0.839	0.081	0.004	0.678
$P_{lower,dep}$				
E_{in}	0.672	0.035	0.004	0.345
E_{in}, S_{low}	0.688	0.038	0.004	0.376
$P_{raise,dep}$				
S_{low}	0.854	0.105	0.006	0.708

For raising actions upon arrival we find that S_{low} is the most influential variable, while a model with E_{in} fits only poorly. We find, however, that a model with both these variables offers a marginal but significant improvement. This suggests that if the occupants find their blind lowered on arrival they are more concerned with having an unobstructed view than by effective stimuli.

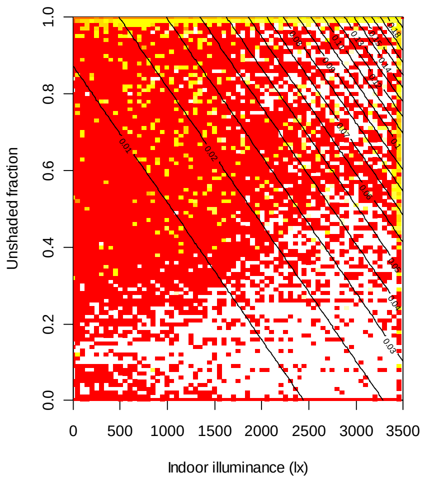

Figure 3 Observed proportion of raising actions on arrival as a function of indoor illuminance and initial unshaded fraction, with logistic regression surface levels

Our final model for actions on arrival on lower blinds is thus:

$$\text{logit}\,(P_{lower,arr}) = -6.734+8.49\cdot10^{-4}\,E_{in}+2.385\,S_{low} \quad (2)$$

$$\text{logit}\,(P_{raise,arr}) = -0.811-2.94\cdot10^{-4}\,E_{in}-4.076\,S_{low} \quad (3)$$

Actions during presence and at departure on the lower blinds

During the survey period both the lowering and raising of blinds occurred in 0.3% of the time steps. Actions on blinds during occupancy are thus particularly rare. As noted earlier no specific behaviour was noticed at departure, so we infer a model for application in both these situations.

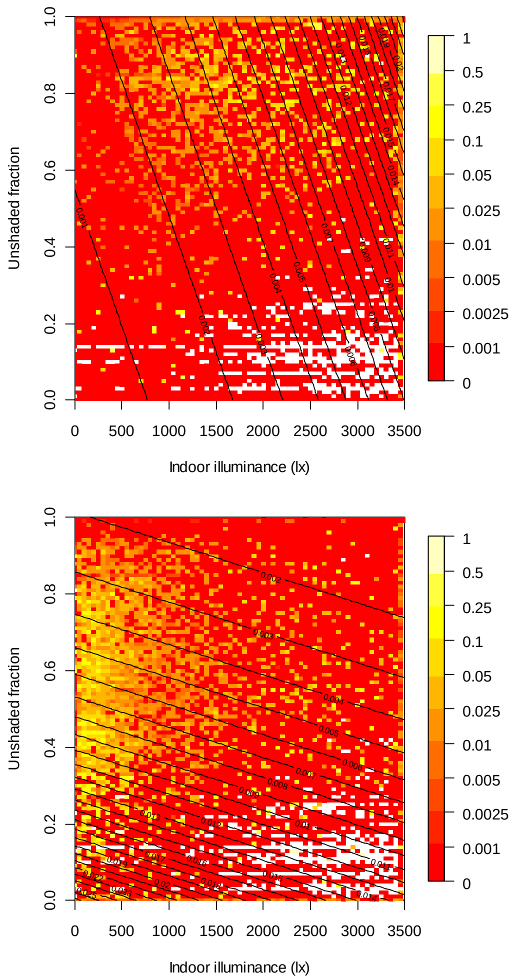

Figure 4 Observed proportion of lowering (top) and raising (bottom) actions during presence as a function of indoor illuminance and initial unshaded fraction, with logistic regression surface levels

The variable selection process retains E_{in} and then S_{low} for lowering probability (Figure 4, top) and S_{low} and then E_{in} for raising (Figure 4, bottom); likewise on arrival. The predicted probabilities are lower than on arrival, which confirms a specific behaviour in this situation:

$$\text{logit}\,(P_{lower,int}) = -7.531+7.57\cdot10^{-4}\,E_{in}+1.147\,S_{low} \quad (4)$$

$$\text{logit}\,(P_{raise,int}) = -3.535-2.05\cdot10^{-4}\,E_{in}-2.582\,S_{low} \quad (5)$$

No particular probability increase was noticed when considering ϕ and α. Goodness-of-fit indicators are lower than on arrival.

We have also examined the possibility of a purely seasonal effect on behaviour at departure, eg. whether occupants preventively lower their blinds when leaving during a heat wave to avoid heat gains during their absence. We did not notice any behaviour of this kind, after examining actions with respect to both daily and monthly mean outdoor temperatures.

Action on arrival on the upper blinds

We have performed similar analyses for the inference of a model for the upper blinds. We found that E_{in}, E_{out} and S_{up} were significant parameters for lowering and raising actions. We obtain thus:

$$\text{logit}(P_{lower,arr}) = -7.164 + 9.37\cdot10^{-4} E_{in} + 5.42\cdot10^{-6} E_{out} + 2.198\, S_{up} \quad (6)$$

$$\text{logit}(P_{raise,arr}) = -1.808 - 3.78\cdot10^{-4} E_{in} - 1.91\ 10^{-5} E_{out} - 3.828\, S_{up} \quad (7)$$

Table 2
Upper blinds – Goodness-of-fit estimators for the upper blinds for logistic models including one or several variables

VARIABLES	AUC	R^2	B	D_{XY}
$P_{lower,arr}$				
E_{in}	0.772	0.146	0.035	0.543
E_{in}, S_{up}	0.819	0.193	0.034	0.638
E_{in}, S_{up}, E_{out}	0.856	0.222	0.024	0.712
$P_{raise,arr}$				
S_{up}	0.839	0.210	0.027	0.678
S_{up}, E_{in}	0.857	0.221	0.026	0.714
S_{up}, E_{in}, E_{out}	0.881	0.235	0.017	0.761
S_{up}, E_{in}, E_{out}, S_{low}	0.887	0.244	0.017	0.775
$P_{lower,int}$				
E_{in}	0.778	0.082	0.005	0.557
E_{in}, S_{up}	0.797	0.098	0.005	0.594
E_{in}, S_{up}, E_{out}	0.814	0.115	0.004	0.628
$P_{raise,int}$				
S_{up}	0.764	0.083	0.004	0.529
S_{up}, E_{in}	0.792	0.092	0.004	0.584
S_{up}, E_{in}, E_{out}	0.830	0.130	0.003	0.660
$P_{lower,dep}$				
E_{in}	0.740	0.060	0.006	0.480
E_{in}, E_{out}	0.781	0.081	0.004	0.562
E_{in}, E_{out}, S_{up}	0.811	0.107	0.004	0.621
$P_{raise,dep}$				
S_{up}	0.803	0.106	0.008	0.606
S_{up}, E_{in}	0.803	0.111	0.008	0.606
S_{up}, E_{in}, E_{out}	0.845	0.143	0.007	0.689

Action during presence and at departure on the upper blinds

We find that action probabilities for both lowering and raising actions should include E_{in}, E_{out} and S_{up} (Table 2), which gives the following action probabilities:

$$\text{logit}(P_{lower,int}) = -8.146 + 8.26\cdot10^{-4} E_{in} + 5.64\cdot10^{-6} E_{out} + 1.520\, S_{up} \quad (8)$$

$$\text{logit}(P_{raise,int}) = -3.656 - 2.55\cdot10^{-4} E_{in} - 1.71\cdot10^{-5} E_{out} - 3.233\, S_{up} \quad (9)$$

For all these sub-models, the inclusion of E_{out} brings significant additional predictive value (Table 2), which was not the case for the lower blinds. This most likely relates to the particular prupose of the anidolic reflector to enhance internal daylight levels whilst E_{out} is low (and to prevent excess internal illumination whilst E_{out} is high).

Choice of shaded fraction

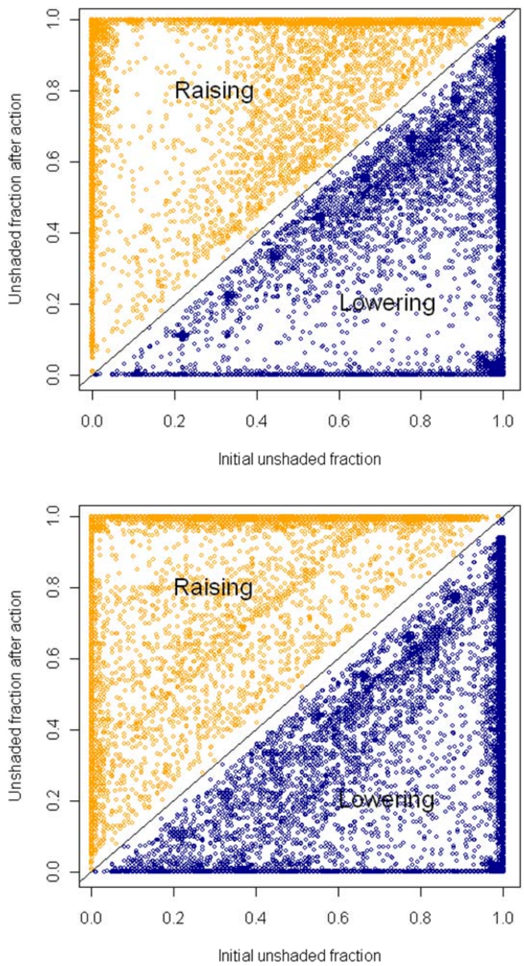

Figure 5 Observed transitions between shaded fractions for lower (top) and upper (bottom) blinds, using jittered values for better visualisation

We studied occupants' choices of shaded fraction when performing an action and observed that they differ greatly in terms of whether they perform a lowering or raising action. Generally, when occupants raise their blinds, little care is taken about the choice of a final shaded fraction, and blinds are often raised until their maximum. This is less the case for lowering actions, where care is taken to maintain view and a suitable internal illuminance, which makes full lowerings more rare than full raisings. Observed transitions are shown in Figure 5.

Once again we have used forward selection to identify key variables to infer a distribution for the probability of fully lowering and fully raising blinds, retaining E_{out} and S_{low} as predictors:

$$\text{logit}\ (P_{lower,full}) = -0.27 + 9.08 \cdot 10^{-7} E_{out} - 2.232 S_{low}, \quad (10)$$

$$\text{logit}\ (P_{raise,full}) = 4.35 - 2.31 \cdot 10^{-5} E_{out} + 1.346\ S_{low}, \quad (11)$$

and E_{out} and S_{up} for upper blinds:

$$\text{logit}\ (P_{lower,full}) = -4.35 + 2.50 \cdot 10^{-6} E_{out} + 0.15\ S_{up}, \quad (12)$$

$$\text{logit}\ (P_{raise,full}) = 1.543 - 2.12 \cdot 10^{-5} E_{out} - 0.56\ S_{up}. \quad (13)$$

IMPLEMENTATION

Based on these results, we have developed a simple algorithm for the simulation of blinds usage, which consists of the following steps (see Figure 6):

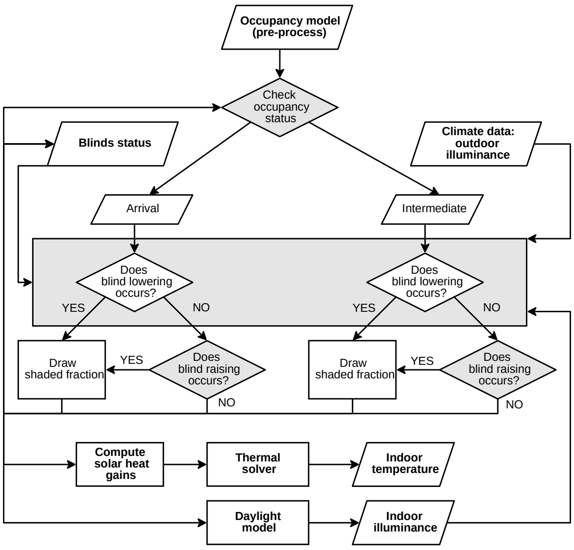

Figure 6 Simplified scheme for implementation of the blind usage algorithm

- The occupancy status is checked. If no occupant is present, the state of blinds remains constant.
- If $P_{lower} \geq P_{raise}$, we use the Monte-Carlo method on P_{lower} to determine whether the blind is to be lowered. If no lowering is predicted, the Monte-Carlo method determines whether a raising occurs through P_{raise}. The order of this procedure is inverted if $P_{lower} < P_{raise}$.
- If an action was performed, the new shaded fraction is drawn from the relevant distribution.

VALIDATION

In order to validate our model we have performed 10 repeated simulations using 5 minutes time steps for the whole period with available measurements and for the 12 measured offices, producing 10 × 12 = 120 sets of simulated lower and upper unshaded fractions ($S_{low,sim}(t)$, $S_{up,sim}(t)$), to be compared with 12 sets of observed states ($S_{low,obs}(t)$, $S_{up,obs}(t)$).

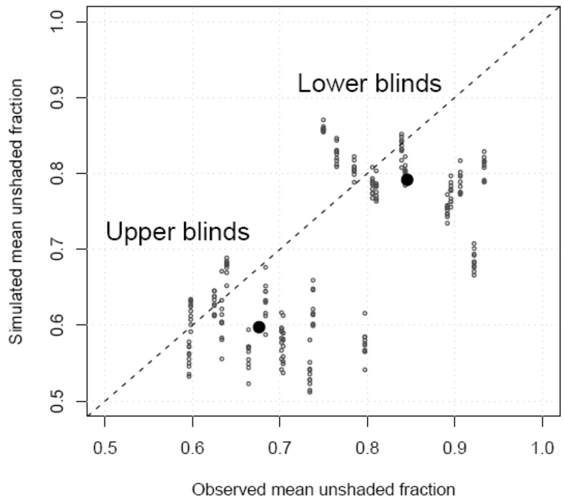

Figure 7 Observed versus ten simulated mean unshaded fractions for all offices

The simulated mean unshaded fraction ($<S_{low,sim}>$, $<S_{up,sim}>$) = (0.792, 0.597) is reliable, although slightly lower than observed ($<S_{low,obs}>$, $<S_{up,obs}>$) = (0.846, 0.676), see Figure 7. The simulated distribution of unshaded fractions for lower blinds (Figure 8) reproduces reliably the observed levels, with low spread among simulation replicates. However, the predicted proportion of 'fully' lowered and raised blinds is slightly too low.

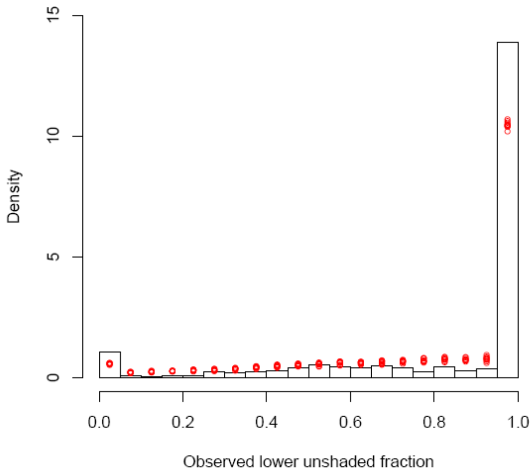

Figure 8 Histograms of observed (black) and simulated (red) unshaded fractions

DISCUSSION

Like most previous surveys, our measurements come from a single configuration of blinds, which potentially limits the generality of our results. There is a great diversity in the available types of shading devices, and differences in their use are evident (eg. occupants may interact differently with curtains, blinds with blades, Venetian blinds or shutters). Furthermore, our data are also currently restricted to an office type environment; in which the importance of other factors such as privacy may not be as high as they are in the home. The type of control may also play a role, as occupants of our survey may easily adjust their blinds through a single press on a button. We cannot exclude that the ease of use of shading devices influence the probabilities of action.

These issues bring out the necessity to find a generalist method. Nevertheless, our approach based on local stimuli (indoor horizontal illuminance) offers promise for extension to other configurations of shading devices. Indeed we may expect to find the same driving variables, but with different action probabilities depending on shading device accessibility.

Our transition probabilities do not include outdoor radiation parameters such as $I_{gl,hor}$, $I_{diff,hor}$ or I_{beam}. Our statistical analyses showed that the relevant visual stimuli are already included with E_{in}. Furthermore, even if they were found to be more influential, their use would be problematic as their influence on occupants' actions varies with the glazed surface and the current shaded fraction, which would make their prediction purely specific to our building. The use of indoor visual stimuli is thus more coherent, provided that a daylight model is coupled with simulations.

ACKNOWLEDGEMENT

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NOMENCLATURE

θ_{in}	Indoor temperature (°C)
θ_{out}	Outdoor temperature (°C)
E_{in}	Indoor horizontal illuminance (lx)
E_{out}	Outdoor horizontal illuminance (lx)
$I_{gl,hor}$	Outdoor global horizontal irradiance (W/m^2)
$I_{diff,hor}$	Outdoor diffuse horizontal irradiance (W/m^2)
I_{beam}	Outdoor beam irradiance (W/m^2)
ϕ, α	Sun elevation (°), sun azimuth (°)
f_L	Electrical lighting on (binary)
S_{low}, S_{up}	Lower and upper unshaded fractions

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